In the claims:

1. (currently amended) A method of modifying HMM models trained on clean speech with cepstral mean normalization to provide models that compensate for simultaneous channel/microphone distortion and background noise (additive distortion) comprising the steps of:

providing HMM models trained on clean speech with cepstral mean normalization;

for each speech utterance calculating the mean mel-scaled cepstrum coefficients (MFCC) vector ~~$\hat{b}$~~ b over the clean database;

adding the mean MFCC vector ~~$\hat{b}$~~ b to the mean vectors $m_{p,j,k}$ of the original HMM models where p is the HMM index ~~of PDF~~, j is the state index, and k the mixing component index, to ~~get in~~ obtain non-CMN mean vectors ~~$m_{p,j,k}$~~ $\overline{m}_{p,j,k}$;

for a given speech utterance calculating an estimate of the background noise vector $\tilde{X}$;

calculating the model mean vectors $\hat{m}_{p,j,k}$ adapted to the noise $\tilde{X}$ using $\hat{m}_{p,j,k} = \mathrm{IDFT}(\mathrm{DFT}(\overline{m}_{p,j,k} \oplus \mathrm{DFT}(\tilde{X}))$ to get the noise compensated mean vectors; ~~where the Inverse Discrete Fourier Transform is taken sum of the Discrete Fourier Transform of the mean vectors $\overline{m}_{p,j,k}$ modified by the mean MFCC vector $\hat{b}$ added to the Discrete Fourier Transform of the estimated noise $\tilde{X}$;~~ and

calculating the mean vector $\hat{b}$ of the noisy data over the noisy speech space, and removing the mean vector $\hat{b}$ of the noisy data from the model mean vectors adapted to noise to ~~get~~ obtain the target HMM model mean vectors and

modifying said HMM models to compensate simultaneously for convolutive distortion and background noise using said HMM model mean vectors.

2. (currently amended) The method of Claim 1 wherein the step of calculating the mean vector $\hat{b}$ of the noisy data over the noisy speech space will calculate the vector using statistics of noisy models using : $\hat{b} = \sum_{p}\sum_{j}\sum_{k} P_{\mathcal{H}}(p)P_{J\mid\mathcal{H}}(j\mid p)P_{\mathcal{K}\mid\mathcal{H}J}(k\mid p,j)\hat{m}_{p,j,k}$ where $\mathcal{H}$ is the variable denoting ~~PDF Index~~ HMM index, ~~J~~ J is the variable for the ~~sate~~ state index and $\mathcal{K}$ is the variable for mixing component index

3. (original) The method of Claim 2 wherein said calculating the mean vector $\hat{b}$ uses equal probabilities for $P_{\mathcal{H}}(p)$

$$P_H(p) = C.$$

4. (currently amended) The method of Claim 2 wherein equal probabilities for $P_{\mathcal{H}}(p)$, $P_{J\mid\mathcal{H}}P(J\mid p)$ and $P_{\mathcal{K}\mid\mathcal{H}J}(k\mid p,j)$ *is* used [[.]]

$$P_{\mathcal{H}}(p) = C$$

$$P_{J\mid\mathcal{H}}(j\mid p) = D$$

$$P_{\mathcal{K}\mid\mathcal{H}J}(k\mid p,j) = E.$$

5. (original) The method of Claim 3 wherein mean vector $\hat{b}$ becomes equal to:

$$\hat{b} = IDFT\,(DFT(\mathbf{b}) \oplus DFT\,(\tilde{X})).$$

6. (currently amended) A method of speech recognition with compensation for channel distortion and background noise comprising the steps of:

providing HMM models trained on clean speech with cepstral mean normalization;

for ~~each utterance~~ all utterances of the training database:

calculating the ~~calculating the~~ mean mel-scaled cepstrum coefficients (MFCC) vector ~~$\hat{b}$~~ b over the clean database;

adding the mean MFCC vector $\hat{b}$ b to the mean vectors $m_{p,j,k}$ of the original HMM models where p is the index of HMM ~~PDF~~, j is the state, and k the mixing component to ~~get in~~ obtain ~~$m_{p,j,k}$~~ $\hat{m}_{p,j,k}$;

for a given speech utterance calculating an estimate of the background noise vector $\tilde{X}$;

calculating the model mean vectors adapted to the noise $\tilde{X}$ using $\hat{m}_{p,j,k}$ = IDFT (DFT ($\overline{m}_{p,j,k}$ $\oplus$ DFT ($\tilde{X}$)) to get the noise compensated mean vectors ~~where the Inverse Discrete Fourier Transform is taken sum of the Discrete Fourier Transform of the mean vectors $\overline{m}_{p,j,k}$ modified by the mean MFCC vector $\hat{b}$ added to the Discrete Fourier Transform of the estimated noise $\tilde{X}$~~; and

calculating the mean vector $\hat{b}$ of the noisy data over the noisy speech space, and removing the mean vector $\hat{b}$ of the noisy data from the model mean vectors adapted to noise to get the target model; and

comparing the target model to the speech input utterance to recognize speech.

7. (currently amended) The method of Claim 6 wherein the step of calculating the mean vector $\hat{b}$ of the noisy data over the noisy speech space will calculate the vector using statistics of noisy model using : $\hat{b} = \sum_p \sum_j \sum_k P_H(p) P_{J|H}(j \mid p) P_{\mathcal{K}|H,J}(k \mid p,j)\, \hat{m}_{p,j,k}$ where $\mathcal{H}$ is the variable denoting ~~PDF Index~~ HMM index, ~~J~~ J is the variable for the ~~sate~~ state index and $\mathcal{K}$ is the variable for mixing component index

8. (original) The method of Claim 7 wherein said calculating the mean vector $\hat{b}$ uses equal probabilities for $P_{\mathcal{H}}(p)$

$$P_{\mathcal{H}}(p) = C.$$

9. (currently amended) The method of Claim 7 wherein equal probabilities for $P_{\mathcal{H}}(p)$, $P_{J\,|\,\mathcal{H}}P(j\,|\,p)$ and $P_{\mathcal{K}\,|\,\mathcal{H}J}(k\,|\,h,j)$ *is* used ~~[[.]]~~

$$P_{\mathcal{H}}(p) = \mathrm{C}$$
$$P_{J\,|\,\mathcal{H}}(j\,|\,p) = \mathrm{D}$$
$$P_{\mathcal{K}\,|\,\mathcal{H}J}(k\,|\,p,j) = \mathrm{E}$$

10. (original) The method of Claim 9 wherein mean vector $\hat{\mathrm{b}}$ becomes equal to:

$$\hat{\mathrm{b}} = IDFT\,(DFT(\mathbf{b}) \oplus DFT\,(\widetilde{\mathrm{X}})).$$

11. (currently amended) A speech recognizer with compensation for channel distortion and background noise comprising in combination:

adapted HMM models generated by modifying HMM models trained on clean speech with cepstral mean normalization wherein said models are adapted by:

for ~~each utterance~~ all utterances of the training database:

calculating the calculating the mean mel-scaled cepstrum coefficients (MFCC) vector ~~$\hat{\mathrm{b}}$~~ b over the clean database;

adding the mean MFCC vector b ~~$\hat{\mathrm{b}}$~~ to the mean vectors $\mathrm{m}_{p,j,k}$ of the original HMM models where p is the index of HMM ~~PDF~~, j is the state, and k the mixing component to ~~get in~~ obtain ~~m~~ $\hat{\mathrm{m}}_{p,j,k}$;

for a given speech utterance calculating an estimate of the background noise vector $\widetilde{\mathrm{X}}$;

calculating the model mean vectors adapted to the noise $\widetilde{\mathrm{X}}$ using $\hat{\mathrm{m}}_{p,j,k}$ = IDFT (DFT ($\overline{\mathrm{m}}_{p,j,k} \oplus$ DFT ($\widetilde{\mathrm{X}}$)) to get the noise compensated mean vectors ~~where the Inverse Discrete Fourier Transform is taken sum of the Discrete Fourier Transform of the~~

~~mean vectors $\overline{m}_{p,j,k}$ modified by the mean MFCC vector $\hat{b}$ added to the Discrete Fourier Transform of the estimated~~

~~noise $\widetilde{X}$~~; and

calculating the mean vector $\hat{b}$ of the noisy data over the noisy speech space, and removing the mean vector $\hat{b}$ of the noisy data from the model mean vectors adapted to noise to get the adapted model; and

means for comparing the adapted model to the speech input utterance to recognize the input speech.

12. (currently amended) The recognizer of Claim 11 wherein the step of calculating the mean vector $\hat{b}$ of the noisy data over the noisy speech space will calculate the vector using statistics of noisy model using : $\hat{b} = {}_{N}{}^{y}\sum_{p}\sum_{j}\sum_{k} P_{\mathcal{H}}(p)P_{J|\mathcal{H}}(j\,|\,p)P_{\mathcal{K}\,|\,\mathcal{H},J}(k\,|\,p,j)\,\hat{m}_{p,j,k}$ where $\mathcal{H}$ is the variable denoting ~~PDF Index~~ HMM index, ~~J~~ J is the variable for the ~~sate~~ state index and $\mathcal{K}$ is the variable for mixing component index ~~6.~~ ~~The model of Claim 5 wherein the step of calculating the mean vector $\hat{b}$ of the noisy data over the noisy speech space will calculate the vector using statistics of noisy model using :~~

~~$\hat{b} = \sum_{p}\sum_{j}\sum_{k} P_{\mathcal{H}}(p)P_{J|\mathcal{H}}(j\,|\,p)P_{K|\mathcal{H},J}(k\,|\,p,j)\,\hat{m}_{p,j,k}$ where $\mathcal{H}$ is the variable denoting PDF Index J is the variable for the sate index and $\mathcal{K}$ K is the variable for mixing component index~~

13. (original) The recognizer of Claim 12 wherein said calculating the mean vector $\hat{b}$ uses equal probabilities for $P_{\mathcal{H}}(p)$

$$P_{\mathcal{H}}(p) = C.$$

14. (currently amended) The recognizer of Claim 12 wherein equal probabilities for $P_{\mathcal{H}}(p)$, $P_{J|\mathcal{H}}(j\,|\,p)$ and $P_{\mathcal{K}\,|\,\mathcal{H},J}(k\,|\,h,j)$ ~~is~~ is used [[.]]

$$P_{\mathcal{H}}(p) = C\ [[.]]$$

$$P_{J|\mathcal{H}}(j|p) = \mathrm{D}$$

$$P_{\mathcal{K}|\mathcal{HJ}}(k|p,j) = \mathrm{E}$$

15. (original) The method of Claim 12 wherein mean vector $\hat{\mathrm{b}}$ becomes equal to:

$$\hat{\mathrm{b}} = IDFT\,(DFT(\mathbf{b}) \oplus DFT\,(\widetilde{\mathrm{X}})).$$

16. (currently amended) A method of speech recognition with simultaneous compensation for both channel/~~micriphone~~<u>microphone</u> distortion and background noise comprising the steps of:

modifying HMM models trained on clean speech with cepstral mean normalization;

for ~~each speech~~ <u>all training speech</u> utterance<u>s</u> calculating the MFCC vector for a clean database;

adding this mean MFCC vector to the original HMM models;

estimating the background noise for a given speech utterance;

determining the model mean vectors adapted to the noise;

determining the mean vector of the noisy data over the noisy speech space; and

removing the mean vector of the noisy data over the noisy speech space from the model mean vectors adapted to the noise to get the target model.

17. (cancel) A method of speech comprising the steps of:

providing HMM models trained on clean speech with cepstral mean normalization; and

modifying HMM models to compensate silutaneously for convolutive distortion and background noise.